Real Time Identification of Toxic Gases Based on Artificial Neural Networks

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ABSTRACT

The assessment of air pollution using sensors is yet widespread, especially indoor air quality. Artificial Neural Networks (ANNs) constitutes a commonly used approach for the identification of air pollutants. In this paper, we propose the development of Multi-Layer Perceptron (MLP) Neural Network on-line type for the real time identification. For this reason, we used the data base obtained from the multi-sensor system designed for detection of three toxic gases. Compared with some previous research which used multiple linear regression methods and MLP off-line type , our model is proved to be much more successful in terms of the correct identification in real time even with low concentration (one part per million) with better mean square errors (MSE $< 4.10^{-04}$) .

Keywords: *Toxic gases, Artificial Neural Networks, Multi-Layer Perceptron, On-line learning, Real Time Identification.*

I. INTRODUCTION

In recent years, Neural Network models have been developed and successfully applied to atmospheric pollution modeling in general [1-2] and air quality problems in particular [2-8]. Unlike other modeling techniques, Artificial Neural Networks (ANN) is capable of modeling highly non-linear relationships [9-10].The ANNs performance is superior when compared to statistical methods such as multiple linear regression [11,12]. Among the various NN-based models, the feed-forward Neural Network, also known as the Multi Layer Perceptron type Neural Network (MLPNN), is the most commonly used and has been applied to solve many difficult and diverse problems [13–17].

Our approach in this paper consists of training a MLPNN for the identification of toxic gases in a real time manner. For this, we used a database obtained from a multi-sensor system which consists of six chemical sensors of type TGS (called electronic noses) based on metal oxide [18]. Each sensor emits an electrical signal characterized by three variables: Accordingly, a) the initial conductance (G0), b) the dynamic slope of the conductance (dGS/dt) , and c) the steady-state conductance GS [2, 18-20].

The first step consists of a careful selection of adequate parameters of the structure, namely architecture, functions activation, and weights of the neurons by our developed method of neural network (MLP) to find out the right settings for each implementation of these networks. The second step is meant to examine the performance of this model which allows us to compare it with previously developed models [21-22] in terms of correct identification.

The present study aims at developing a quick and easily reliable method to classify and identify the low concentration toxic gases, in real time.The study is significant by virtue of three major benefits: The first is that the application of the on-line learning can be used for the security of air quality in real-time. The second is to select a stable optimum design with a minimum of hidden layers and the neurons in each layer. The last advantage is to prove the power of odor evaluation system (electronic nose) even with low concentration (one Part per Million).

The rest of the paper is organized as follows: The second section is called Materials and Methods. It deals mainly with feature extraction and artificial neural networks. This latter is about the general properties of the trained ANNs consisting of developed MLP algorithm. The third part is devoted to the results and discussions of the performance of our model during learning and testing phases. In the last section, we will draw some conclusions and suggest future research.

II. MATERIAL AND METHODS

2.1. Feature extraction

The features obtained for data analysis were extracted from the temporal responses of the sensor array realized by [18] for the detection of the toxic gases H2S (hydrogen sulfide), NO2 (nitrogen dioxide) and their mixture (H2S- NO2).

The sensor array comprised six TGS-XX (with XX = 800, 813, 822, 825, 832 and 2105),Taguchi Gas Sensor obtained from Figaro Engineering, Incorporation [23]. We want to better exploit the information obtained from each experiment.

To achieve this aim, both the traditional steady state response but also additional features that can better characterize the sensor and analysis system were used. For every sensor within the array and measurement performed, three representative features from the response signal were extracted:

• G0: the initial conductance of a sensor calculated as the average value of its conductance during the first minute of the measurement.

• Gs: the steady-state conductance calculated as the average value of its conductance during the latest minute of a measurement.

• dG/dt: the dynamic slope of the conductance calculated between 2 and 50 min of a measurement. This corresponds to a phase where a fast increase of sensor conductance is observed [24].

These three features were extracted from the response of each sensor. Given the fact that there were 6 sensors within the array, each measurement was described by 18 features.

2.2. Artificial neural networks (ANNs)

Artificial Neural Networks (ANNs) are a set of mathematical, statistical and computational methods inspired by nerve cells (neurons) [24-25].Then emergent properties to solve problems once described as complex.ANNs use a high number of units (neurons) interconnected among them by using a connectionist approach to computation. They are needed sets of data, which are differenced in inputs and outputs [26], Figure.1.

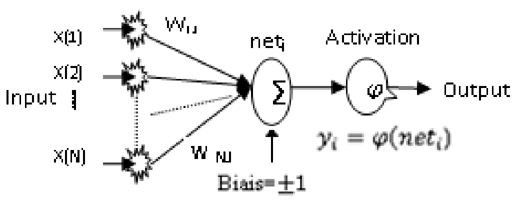

Figure 1: Neural network model

The way of using ANNs has two parts. One is called “training”, and as the own word says, it consists on a process where the system is able to identify the different inputs with the outputs, and their relations. It is said that the system is, in certain way, “learning”. In the second part, (testing), the ANN provides an output when new inputs are introduced. This answer is based on the information that the own system was able to catch in training part. New outputs will be correct if the inputs used for training and testing are similar [27 -28].

2.2.1 Multi-layer perception (MLP) neural network.

The MLP is the most frequently used neural network technique, which makes it possible to carry out the most various applications. The identification of the MLP neural networks requires two types of stages. The first is the determination of the network structure. Different networks with one layer hidden have been tried, and the activation function used in this study is the sigmoid function describedas: $\varphi_i(x) = \frac{1}{1+e^{-\alpha_i x}}$ (1), with $\alpha_i = \alpha_1, \alpha_2$ and α_3(see Table 1.and Figure 2.).

The second stage is the identification (testing) of the three toxic gases, by using back-propagation neural networks (a Matlab based algorithm was developed in our laboratory), [29].

2.2.2 Training algorithm

The MLP network training can be viewed as a function approximation problem in which the network parameters (weights and biases) are adjusted, during the training, in an effort to minimize error function between the network output and the desired output [30-31]. Among these, the most popular and widely used ANNs training algorithm is the Back Propagation (BP) [32, 33]. The BP method, also known as the error back propagation algorithm, is based on the error correlation learning rule [34]. The BP neural networks are trained with different training algorithms. In this section we describe one of these algorithms. The BP algorithm uses the gradients of the activation functions of neurons in order to back-propagate the error that is measured at the output of a neural network and calculate the gradients of the output error over each weight in the network. Subsequently, these gradients are used in updating the ANN weights [35].

The algorithm is described by following rules:

1. Initialization: Set all the weights and biases to small real random values.
2. Presentation of input and desired outputs: Present the Input matrix, x(1), .,x(N) and corresponding desired response d(1),d(2),.,d(N), one pair at a time, where N is the number of training patterns.
3.Calculation of actual outputs: Use Eq. (2) to calculate the output signals $y_1; y_2\ ;\ ; y_{N_M}$

$$y_i = \varphi\left(\sum_{j=1}^{N_{M-1}} W_{ij}\, x_j^{M-1} + b_j^{M-1}\right), i = 1,.N_{M-1}\,. \tag{2}$$

4. Adaptation of weights (w_{ij}) and biases (b_i):

$$W_{ij}^{l-1}(n+1) = W(n) + \Delta W_{ij}^{l-1}(n). \tag{3}$$

$$b_i^{l-1}(n+1) = b_i^{l-1}(n) + \Delta b_i^{l-1}(n) \tag{4}$$

Where $\Delta W_{ij}^{l-1}(n) = \mu x_j(n)\delta_i^{l-1}(n)$. and (5)

$$\Delta b_i^{l-1}(n) = \mu\delta_i^{l-1}(n)\,. \tag{6}$$

and **δ** is the derivative of error function with respect to the weight.

$$\delta = \left({\partial E}/{\partial W}\right) = \left(\frac{\partial E_{MSE}}{\partial W}\right). \tag{7}$$

Where $E_{MSE} = \frac{1}{2}\sum_{i=1}^{k}\left(d_i - y_i(n)\right)^2$, "Learning on line ". (8)

With

$$\delta = \delta_i^{l-1}(n) \begin{cases} \varphi'\left(net_i^{l-1}\right)[d_i - y_i(n)] & ,l = M \\ \varphi'\left(net_i^{l-1}\right)\sum_k W_{ki}\,.\,\delta_k^l & ,1 \le l \le M-1 \end{cases} \tag{9}$$

$$net_i^{l-1} = \sum_{j=1}^{N_{M-1}} W_{ij}\, x_j^{M-1} + b_j^{M-1} \quad . \tag{10}$$

in which $x_j(n)$ = output of node j at iteration n , l is layer, k is the number of output nodes of neural network, M is output layer, and $\boldsymbol{\varphi}$ is the activation function. The learning rate is represented by $\boldsymbol{\mu}$, with $0 < \mu < 1$, [36-37].

2.2.3. The model and parameters used in the study.

Our choice is focused on a multi-layer non-recurring network, based on the learning algorithm of back propagation. The purpose of this learning algorithm is to minimize the mean square errors (MSEs). The network consists of two hidden layers of neurons. The first hidden layer contains 36 neurons. To increase the accuracy, we chose a second hidden layer in which we varied the number of neurons from 1 to 18. We retain the essential elements in Table 1.

Table.1. Architectures and parameters of ANN used in this study

<table>
<tr><td>Neural NetWork</td><td colspan="2">MLP (MULTILAYER PERCEPTRON)Feed Forever, fully Connected (Learning on- line).</td></tr>
<tr><td>Input (I)</td><td colspan="2">I: (matrix of (6x3), 6 sensors each with three variables : G0, dG/dt, Gs.</td></tr>
<tr><td>Output (O)</td><td colspan="2">O (3x1), classification and identification three gases:NO_2 ,H_2S and NO_2-H_2S</td></tr>
<tr><td rowspan="2">Architectures of Hidden Layers (Hi)</td><td>-36 neurons in First hidden layer (H1),and from 12 to 18 neurons in Seconde hidden layer (H2).</td><td>Does not Reach the result</td></tr>
<tr><td>-36 neurons in H1,and from 1 to 11 neurons in H2</td><td>Achieved the result only in 3 neurons</td></tr>
<tr><td>Activation Functions</td><td>I-H1: sigmoid,(represented by blue color).
H1-H2: sigmoid (represented by red color).
H2-O: sigmoid (represented by green color).</td><td>Fig.2.</td></tr>
<tr><td>Encoding of classe (Output)</td><td>Classes can also be encoded as follows:</td><td>[1,-1,-1]=NO_2,
[-1,1,-1]=H_2S,
[-1,-1,1]=NO_2-H_2S .</td></tr>
<tr><td>Statistical results of our model</td><td>standard statistical measures:

Accuracy= ($\frac{\text{Number of correctly classified data}}{\text{Total number of data}}$) * 100

Accuracy (classification) = ($\frac{50+50+50}{150}$ * 100) =100%

Accuracy (Identification) = ($\frac{10+9+10}{30}$) * 100 = 96,6%</td><td>Fig.5 and Fig.6.</td></tr>
<tr><td>Learning Errors, Test Errors ,and Number of Iterations(N) respectively</td><td colspan="2">MSE s < 10^{-05} , MSEs < 4.10^{-04} , N< 200 .</td></tr>
<tr><td>Previous research in brief</td><td colspan="2">-Accuracy (classification) = 86%. And Accuracy (Identification) = 74%
-Number of Iterations (N) = 1200.
-Great Architecture : I(18),H1(36 neurons),H2(3 neurons) H3(3 neurons) H4(2 neurons H5(3 neurons) ,and O(3 neurons) , that used learning bach [22].</td></tr>
</table>

III. RESULTS AND DISCUSSION

In this part, the MLP is used to develop a model able to classify and identify toxic gases. The considered database is composed of 180 samples distributed in three classes (NO_2, H_2S and NO_2- H_2S(mixture)). The database is divided in two parts: 80 % used for the learning step, and 20 % are used for testing. The selection of samples used in learning and testing is done randomly.

The testing subset was used to assess the classification accuracy of the MLP after the training process [39, 40]. The error analysis was used to examine the developed of the designed model.

The criterion exploited in this study was the Mean Square Error (MSE). To be concise and straight forward only the results corresponding to the architecture (I/36 Neurons in -H1 / 3 neurons in-H2 / O), as discussed in Table 1 above, are shown. Figure 2 shows the activation functions used in the hidden layers of our selected architecture. Figure 3 shows the on-line training process MSE evolution in terms of training individuals. As we can see, the MSE is very small. The MSE in terms of testing individuals is illustrated in Figure 4 and it takes small values; this shows the efficiency of our neural model.

The results of classification (training individuals) and identification (testing individuals) are shown in Figure 5, and Figure 6. We can easily notice that all individuals are affected to their correct groups.

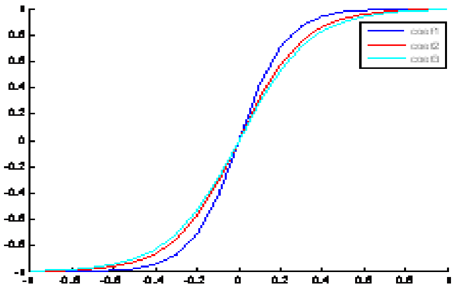

Fig.2.Activation functions used in this study

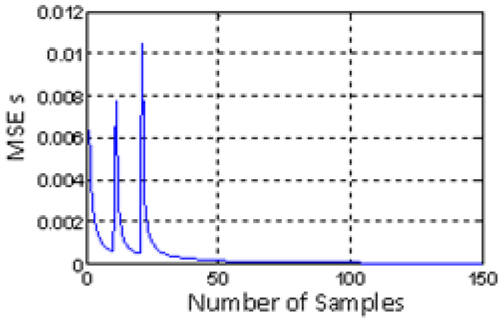

Fig.3. Evolution of the minimums MSEs during learning

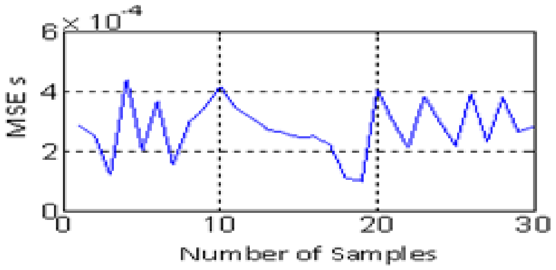

Fig .4.Evolution of the minimums MSEs the during testing

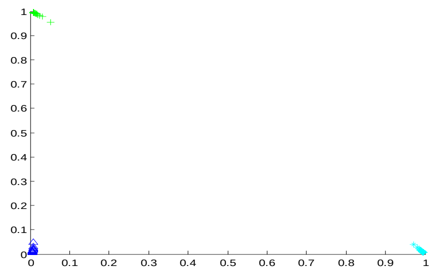

Fig.5.Classification of three toxic gases(learning)

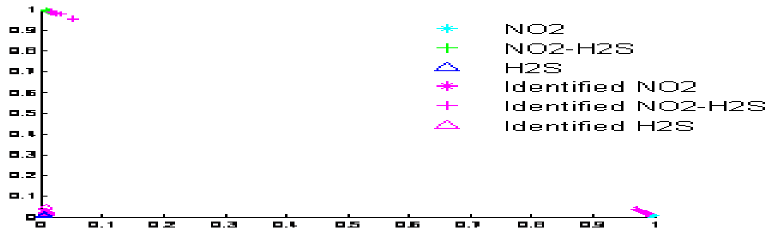

Fig.6.Classification and identification of three toxic gases (testing)

The results obtained have given a better classification and identification. In comparison to previous research which has been effected by great architecture that used learning bach (off-line) toolbox. [21,22].

IV. CONCLUSION AND FUTURE WORK

In this paper, we have studied different architectures to better optimize our design MLP neural network. We have also presented the results of the optimal design. According to these results, our classification reached the rate of 100%, and excellent identification.

The results are very encouraging and show that the smart multisensory systems have a discriminating power of toxic gases at low concentration (1ppm) in real time. This system can be very applicable when there is a danger that cannot be alarmed by human smell sense. The next work will be devoted to the use of an unsupervised neural network model based on the self-organizing map and comparison of performances.

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